Practical Application III: Comparing Classifiers

Overview: In this practical application, your goal is to compare the performance of the classifiers we encountered in this section, namely K Nearest Neighbor, Logistic Regression, Decision Trees, and Support Vector Machines. We will utilize a dataset related to marketing bank products over the telephone.

Getting Started

Our dataset comes from the UCI Machine Learning repository link. The data is from a Portugese banking institution and is a collection of the results of multiple marketing campaigns. We will make use of the article accompanying the dataset here for more information on the data and features.

Problem 1: Understanding the Data

To gain a better understanding of the data, please read the information provided in the UCI link above, and examine the **Materials and Methods** section of the paper. How many marketing campaigns does this data represent?

In [ ]:

Problem 2: Read in the Data

Use pandas to read in the dataset `bank-additional-full.csv` and assign to a meaningful variable name.

In [683…

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from tqdm import tqdm
import seaborn as sns
import plotly.express as px
from sklearn import preprocessing
from sklearn.datasets import load_digits
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.linear_model import BayesianRidge, LogisticRegression
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn import metrics
from sklearn.metrics import classification_report, confusion_matrix
from sklearn.dummy import DummyClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from time import time
from sklearn.metrics import confusion_matrix
from sklearn.metrics import ConfusionMatrixDisplay
from sklearn.svm import SVC
from sklearn.metrics import classification_report, precision_score, recall_score, f1_score
```

In [684…

```
df = pd.read_csv('data/bank-additional-full.csv', sep = ';')
```

In [685…

```
df.head()
```

Out[685…

	age	job	marital	education	default	housing	loan	contact	month	day_of_week	...	campaign	pdays	previous	poutcom
0	56	housemaid	married	basic.4y	no	no	no	telephone	may	mon	...	1	999	0	nonexisten
1	57	services	married	high.school	unknown	no	no	telephone	may	mon	...	1	999	0	nonexisten
2	37	services	married	high.school	no	yes	no	telephone	may	mon	...	1	999	0	nonexisten
3	40	admin.	married	basic.6y	no	no	no	telephone	may	mon	...	1	999	0	nonexisten
4	56	services	married	high.school	no	no	yes	telephone	may	mon	...	1	999	0	nonexisten

5 rows × 21 columns

Problem 3: Understanding the Features

Examine the data description below, and determine if any of the features are missing values or need to be coerced to a different data type.

```
Input variables:
# bank client data:
1 - age (numeric)
2 - job : type of job (categorical: 'admin.','blue-
collar','entrepreneur','housemaid','management','retired','self-
employed','services','student','technician','unemployed','unknown')
3 - marital : marital status (categorical: 'divorced','married','single','unknown'; note:
'divorced' means divorced or widowed)
4 - education (categorical:
'basic.4y','basic.6y','basic.9y','high.school','illiterate','professional.course','university.degree'

5 - default: has credit in default? (categorical: 'no','yes','unknown')
6 - housing: has housing loan? (categorical: 'no','yes','unknown')
7 - loan: has personal loan? (categorical: 'no','yes','unknown')
# related with the last contact of the current campaign:
8 - contact: contact communication type (categorical: 'cellular','telephone')
9 - month: last contact month of year (categorical: 'jan', 'feb', 'mar', ..., 'nov', 'dec')
10 - day_of_week: last contact day of the week (categorical: 'mon','tue','wed','thu','fri')
11 - duration: last contact duration, in seconds (numeric). Important note: this attribute
highly affects the output target (e.g., if duration=0 then y='no'). Yet, the duration is not
known before a call is performed. Also, after the end of the call y is obviously known. Thus,
this input should only be included for benchmark purposes and should be discarded if the
intention is to have a realistic predictive model.
# other attributes:
12 - campaign: number of contacts performed during this campaign and for this client (numeric,
includes last contact)
13 - pdays: number of days that passed by after the client was last contacted from a previous
campaign (numeric; 999 means client was not previously contacted)
14 - previous: number of contacts performed before this campaign and for this client (numeric)
15 - poutcome: outcome of the previous marketing campaign (categorical:
'failure','nonexistent','success')
# social and economic context attributes
16 - emp.var.rate: employment variation rate - quarterly indicator (numeric)
17 - cons.price.idx: consumer price index - monthly indicator (numeric)
18 - cons.conf.idx: consumer confidence index - monthly indicator (numeric)
19 - euribor3m: euribor 3 month rate - daily indicator (numeric)
20 - nr.employed: number of employees - quarterly indicator (numeric)

Output variable (desired target):
21 - y - has the client subscribed a term deposit? (binary: 'yes','no')
```

In [686…

```
df.isnull().sum()
```

Out[686…

```
age               0
job               0
marital           0
education         0
default           0
housing           0
loan              0
contact           0
month             0
day_of_week       0
duration          0
campaign          0
pdays             0
previous          0
poutcome          0
emp.var.rate      0
cons.price.idx    0
cons.conf.idx     0
euribor3m         0
nr.employed       0
y                 0
dtype: int64
```

In [687…

```
df.shape
```

Out[687…

```
(41188, 21)
```

Problem 4: Understanding the Task

After examining the description and data, your goal now is to clearly state the *Business Objective* of the task. State the objective below.

In [688…

```
df.info()
```

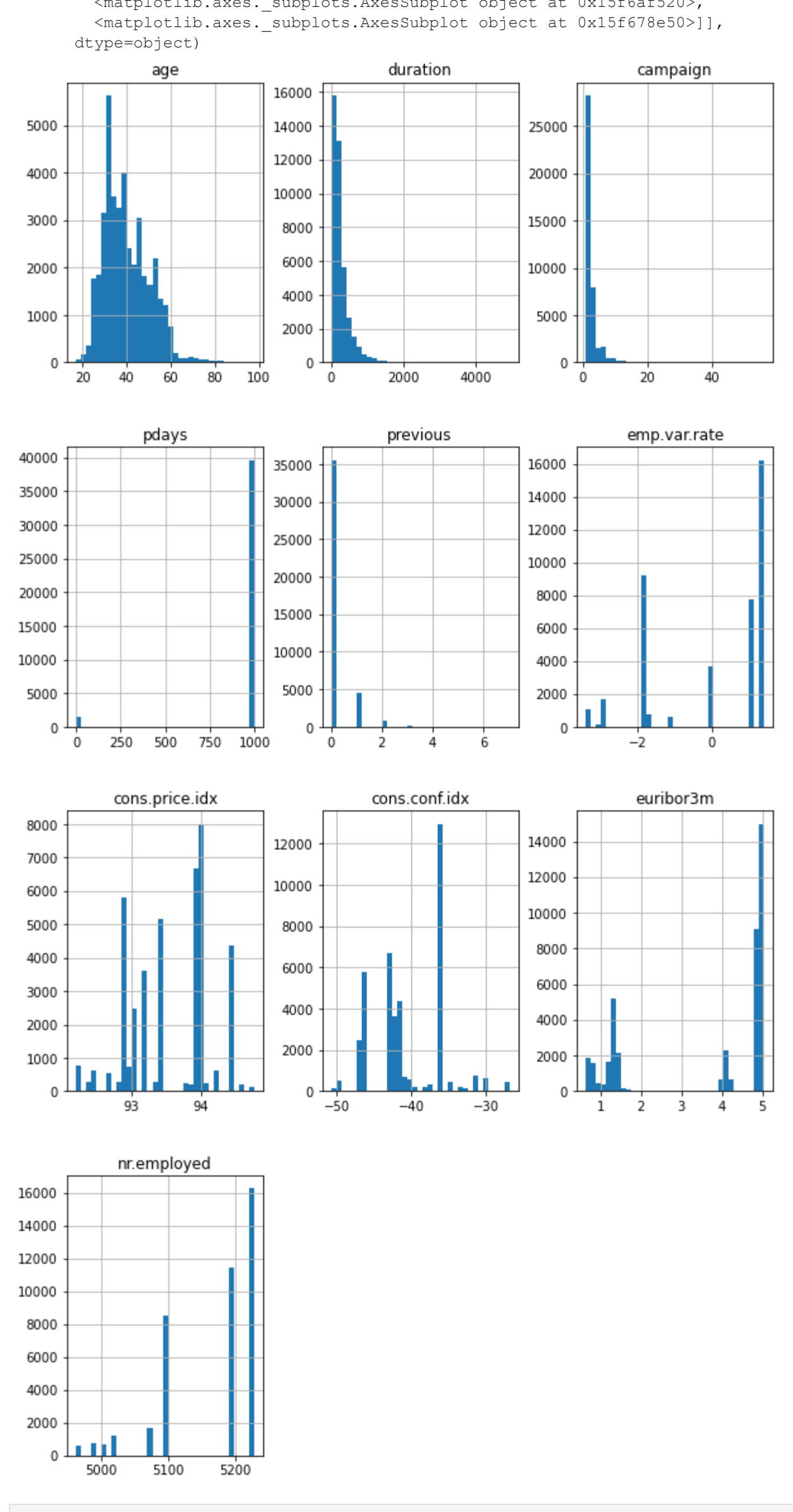
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 41188 entries, 0 to 41187
Data columns (total 21 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   age             41188 non-null  int64
 1   job             41188 non-null  object
 2   marital         41188 non-null  object
 3   education       41188 non-null  object
 4   default         41188 non-null  object
 5   housing         41188 non-null  object
 6   loan            41188 non-null  object
 7   contact         41188 non-null  object
 8   month           41188 non-null  object
 9   day_of_week     41188 non-null  object
 10  duration        41188 non-null  int64
 11  campaign        41188 non-null  int64
 12  pdays           41188 non-null  int64
 13  previous        41188 non-null  int64
 14  poutcome        41188 non-null  object
 15  emp.var.rate    41188 non-null  float64
 16  cons.price.idx  41188 non-null  float64
 17  cons.conf.idx   41188 non-null  float64
 18  euribor3m       41188 non-null  float64
 19  nr.employed     41188 non-null  float64
 20  y               41188 non-null  object
dtypes: float64(5), int64(5), object(11)
memory usage: 6.6+ MB
```

In [689…

```
df.hist(bins=35,figsize=(10,20))
```

Out[689…

```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x15f6c5430>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x165bb4130>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x1658158e0>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x165804100>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x156773820>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x15ca77040>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x15ca77fd0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x1659ce7f0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x1658906a0>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x15d194e20>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x15f6af520>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x15f678e50>]],
      dtype=object)
```



In [690…

```
# create Correlation Matrix to understand the correlation between numeric columns
df.corr()
```

```
<ipython-input-690-078958d9e474>:2: FutureWarning: The default value of numeric_only in DataFrame.corr is depre
cated. In a future version, it will default to False. Select only valid columns or specify the value of numeric
_only to silence this warning.
  df.corr()
```

Out[690…

	age	duration	campaign	pdays	previous	emp.var.rate	cons.price.idx	cons.conf.idx	euribor3m	nr.employed
age	1.000000	-0.000866	0.004594	-0.034369	0.024365	-0.000371	0.000857	0.129372	0.010767	-0.017725
duration	-0.000866	1.000000	-0.071699	-0.047577	0.020640	-0.027968	0.005312	-0.008173	-0.032897	-0.044703
campaign	0.004594	-0.071699	1.000000	0.052584	-0.079141	0.150754	0.127836	-0.013733	0.135133	0.144095
pdays	-0.034369	-0.047577	0.052584	1.000000	-0.587514	0.271004	0.078889	-0.091342	0.296899	0.372605
previous	0.024365	0.020640	-0.079141	-0.587514	1.000000	-0.420489	-0.203130	-0.050936	-0.454494	-0.501333
emp.var.rate	-0.000371	-0.027968	0.150754	0.271004	-0.420489	1.000000	0.775334	0.196041	0.972245	0.906970
cons.price.idx	0.000857	0.005312	0.127836	0.078889	-0.203130	0.775334	1.000000	0.058986	0.688230	0.522034
cons.conf.idx	0.129372	-0.008173	-0.013733	-0.091342	-0.050936	0.196041	0.058986	1.000000	0.277686	0.100513
euribor3m	0.010767	-0.032897	0.135133	0.296899	-0.454494	0.972245	0.688230	0.277686	1.000000	0.945154
nr.employed	-0.017725	-0.044703	0.144095	0.372605	-0.501333	0.906970	0.522034	0.100513	0.945154	1.000000

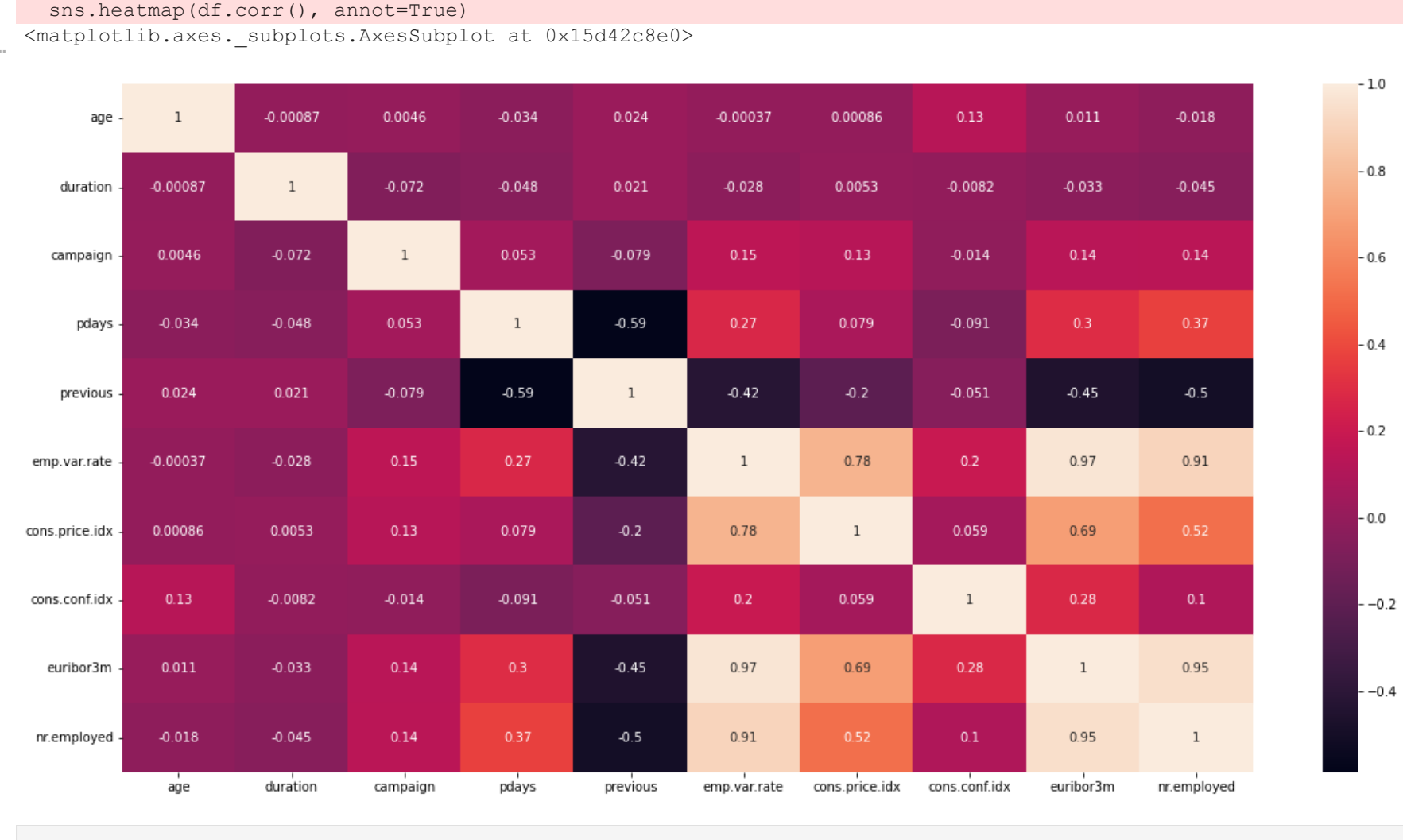
In [691…

```
fig, ax = plt.subplots(figsize=(20,10))
sns.heatmap(df.corr(), annot=True)
```

```
<ipython-input-691-21f4ecc2ce54>:2: FutureWarning: The default value of numeric_only in DataFrame.corr is depre
cated. In a future version, it will default to False. Select only valid columns or specify the value of numeric
_only to silence this warning.
  sns.heatmap(df.corr(), annot=True)
```

Out[691…

```
<matplotlib.axes._subplots.AxesSubplot at 0x15d42c8e0>
```



In [692…

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 41188 entries, 0 to 41187
Data columns (total 21 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   age             41188 non-null  int64
 1   job             41188 non-null  object
 2   marital         41188 non-null  object
 3   education       41188 non-null  object
 4   default         41188 non-null  object
 5   housing         41188 non-null  object
 6   loan            41188 non-null  object
 7   contact         41188 non-null  object
 8   month           41188 non-null  object
 9   day_of_week     41188 non-null  object
 10  duration        41188 non-null  int64
 11  campaign        41188 non-null  int64
 12  pdays           41188 non-null  int64
 13  previous        41188 non-null  int64
 14  poutcome        41188 non-null  object
 15  emp.var.rate    41188 non-null  float64
 16  cons.price.idx  41188 non-null  float64
 17  cons.conf.idx   41188 non-null  float64
 18  euribor3m       41188 non-null  float64
 19  nr.employed     41188 non-null  float64
 20  y               41188 non-null  object
dtypes: float64(5), int64(5), object(11)
memory usage: 6.6+ MB
```

In [693…

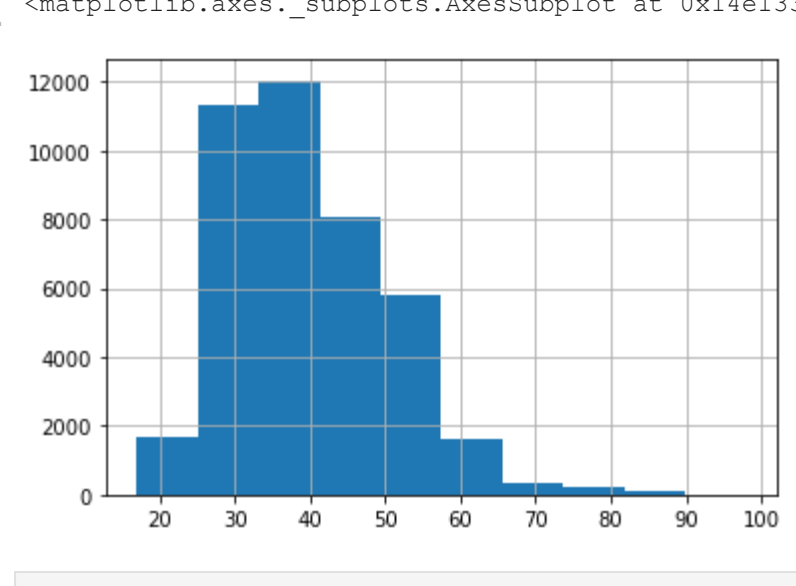
```
num_col = ['age', 'duration', 'campaign', 'pdays', 'previous', 'emp.var.rate', 'cons.price.idx', 'cons.conf.id
cat_cols = ['job', 'marital', 'education', 'default', 'housing', 'loan', 'contact','month', 'day_of_week', 'pou
```

In [694…

```
df["age"].hist(bins=10)
```

Out[694…

```
<matplotlib.axes._subplots.AxesSubplot at 0x14e133220>
```



In [695…

```
print(df["age"].max())
print(df["age"].min())
```

```
98
17
```

In [696…

```
bank_df = df.copy()
```

In [697…

```
bank_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 41188 entries, 0 to 41187
Data columns (total 21 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   age             41188 non-null  int64
 1   job             41188 non-null  object
 2   marital         41188 non-null  object
 3   education       41188 non-null  object
 4   default         41188 non-null  object
 5   housing         41188 non-null  object
 6   loan            41188 non-null  object
 7   contact         41188 non-null  object
 8   month           41188 non-null  object
 9   day_of_week     41188 non-null  object
 10  duration        41188 non-null  int64
 11  campaign        41188 non-null  int64
 12  pdays           41188 non-null  int64
 13  previous        41188 non-null  int64
 14  poutcome        41188 non-null  object
 15  emp.var.rate    41188 non-null  float64
 16  cons.price.idx  41188 non-null  float64
 17  cons.conf.idx   41188 non-null  float64
 18  euribor3m       41188 non-null  float64
 19  nr.employed     41188 non-null  float64
 20  y               41188 non-null  object
dtypes: float64(5), int64(5), object(11)
memory usage: 6.6+ MB
```

In [698…

```
bank_df.describe()
```

Out[698…

	age	duration	campaign	pdays	previous	emp.var.rate	cons.price.idx	cons.conf.idx	euribor3m
count	41188.00000	41188.000000	41188.000000	41188.000000	41188.000000	41188.000000	41188.000000	41188.000000	41188.000000
mean	40.02406	258.285010	2.567593	962.475454	0.172963	0.081886	93.575664	-40.502600	3.621291
std	10.42125	259.279249	2.770014	186.910907	0.494901	1.570960	0.578840	4.628198	1.734447
min	17.00000	0.000000	1.000000	0.000000	0.000000	-3.400000	92.201000	-50.800000	0.634000
25%	32.00000	102.000000	1.000000	999.000000	0.000000	-1.800000	93.075000	-42.700000	1.344000
50%	38.00000	180.000000	2.000000	999.000000	0.000000	1.100000	93.749000	-41.800000	4.857000
75%	47.00000	319.000000	3.000000	999.000000	0.000000	1.400000	93.994000	-36.400000	4.961000
max	98.00000	4918.000000	56.000000	999.000000	7.000000	1.400000	94.767000	-26.900000	5.045000

In [699…

```
# Removing the outliers
first_quartile = df['age'].quantile(.25)
third_quartile = df['age'].quantile(.75)
iqr = third_quartile - first_quartile
lower_quartile = first_quartile - 1.5 *iqr
upper_quartile = third_quartile + 1.5 * iqr
bank_df = df.loc[(df['age']> lower_quartile) & (df['age']<upper_quartile)]
```

In [700…

```
print(bank_df["age"].max())
print(bank_df["age"].min())
```

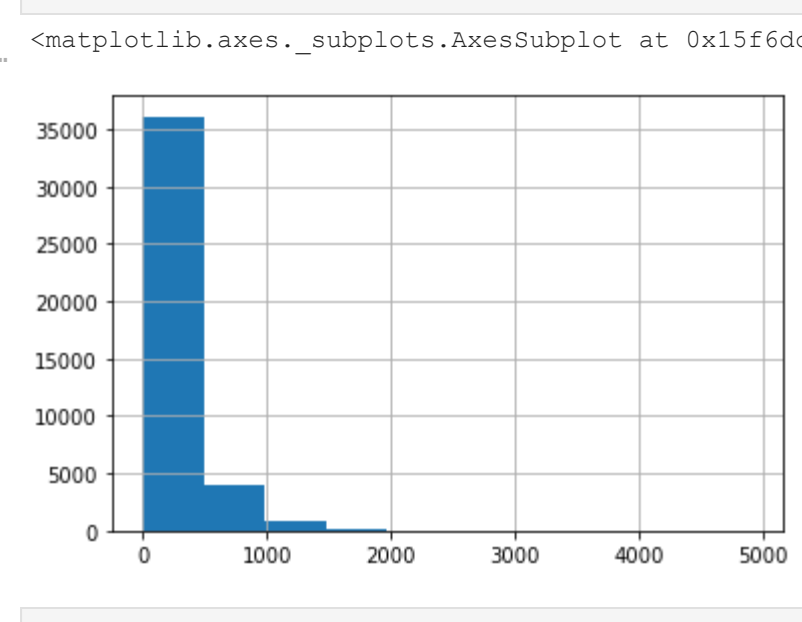
```
69
17
```

In [701…

```
df["duration"].hist(bins=10)
```

Out[701…

```
<matplotlib.axes._subplots.AxesSubplot at 0x15f6dc430>
```



In [702…

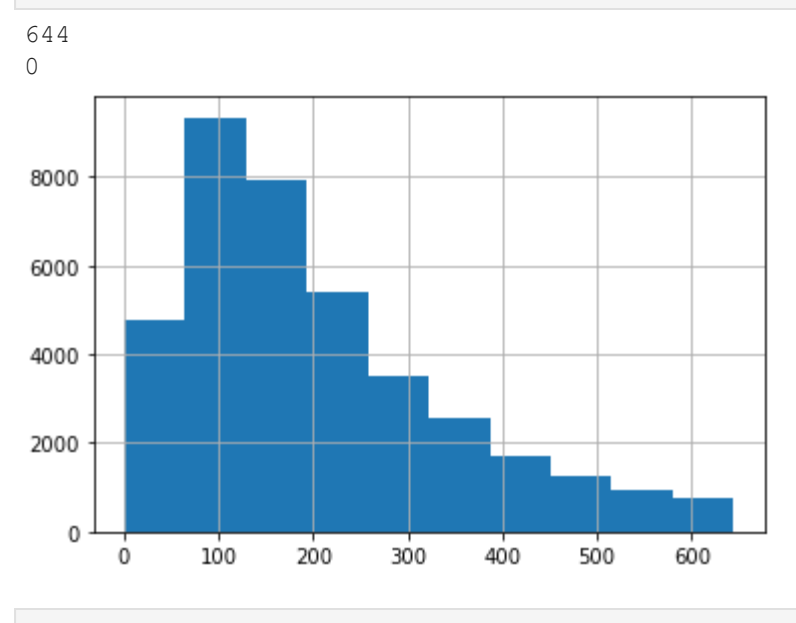
```
# Removing outliers from duration
print(bank_df["duration"].max())
print(bank_df["duration"].min())
first_quartile = bank_df['duration'].quantile(.25)
third_quartile = bank_df['duration'].quantile(.75)
iqr = third_quartile - first_quartile
lower_quartile = first_quartile - 1.5 * iqr
upper_quartile = third_quartile + 1.5 * iqr
bank_df = df.loc[(df['duration']> lower_quartile) & (df['duration']< upper_quartile)]
```

```
4918
0
```

In [703…

```
bank_df["duration"].hist(bins=10)
print(bank_df["duration"].max())
print(bank_df["duration"].min())
```

```
644
0
```



In [704…

```
print(bank_df["campaign"].max())
print(bank_df["campaign"].min())
```

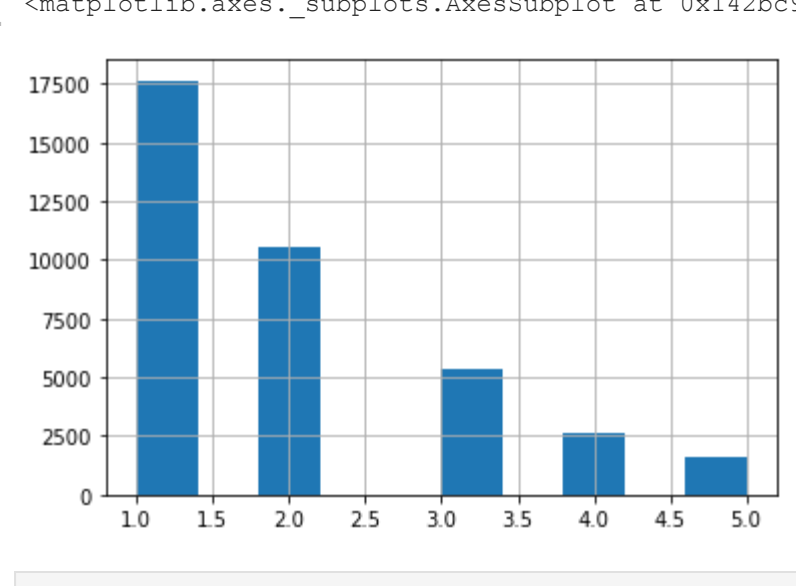
```
56
1
```

In [705…

```
# Remove outliers from the numerical column - campaign using IQR
first_quartile = bank_df['campaign'].quantile(.25)
third_quartile = bank_df['campaign'].quantile(.75)
iqr = third_quartile - first_quartile
lower_quartile = first_quartile - 1.5 * iqr
upper_quartile = third_quartile + 1.5 * iqr
bank_df = df.loc[(df['campaign']> lower_quartile) & (df['campaign']< upper_quartile)]
bank_df["campaign"].hist(bins=10)
```

Out[705…

```
<matplotlib.axes._subplots.AxesSubplot at 0x142bc9940>
```

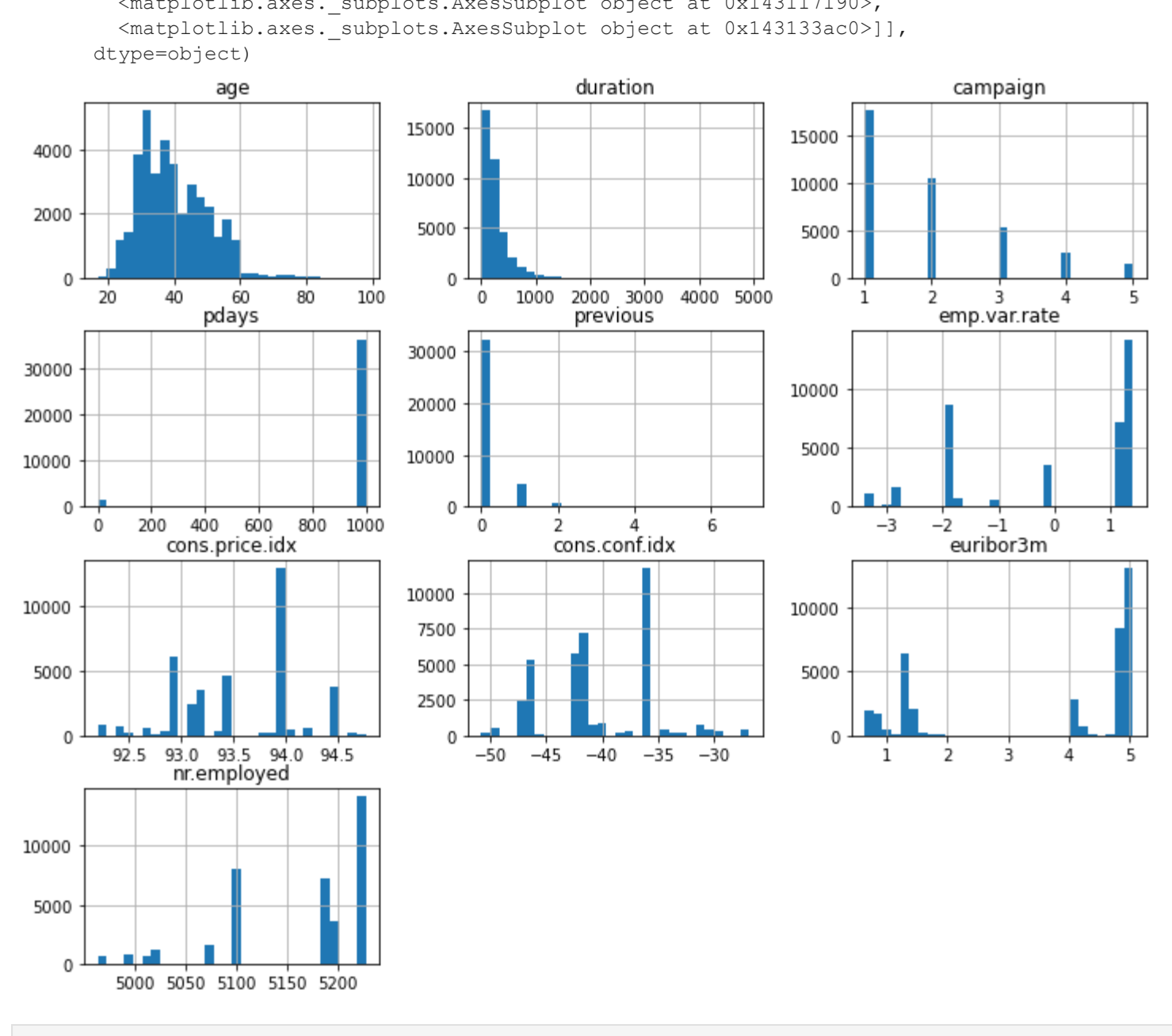


In [706…

```
bank_df.hist(bins=30, figsize=(12, 10))
```

Out[706…

```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x142dbf7f0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x142ddc310>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x142d7f790>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x142194be0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x1421c20d0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x14220b400>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x14220b4f0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x1414619a0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x1427b81f0>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x14293fa90>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x143117190>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x143133ac0>]],
      dtype=object)
```

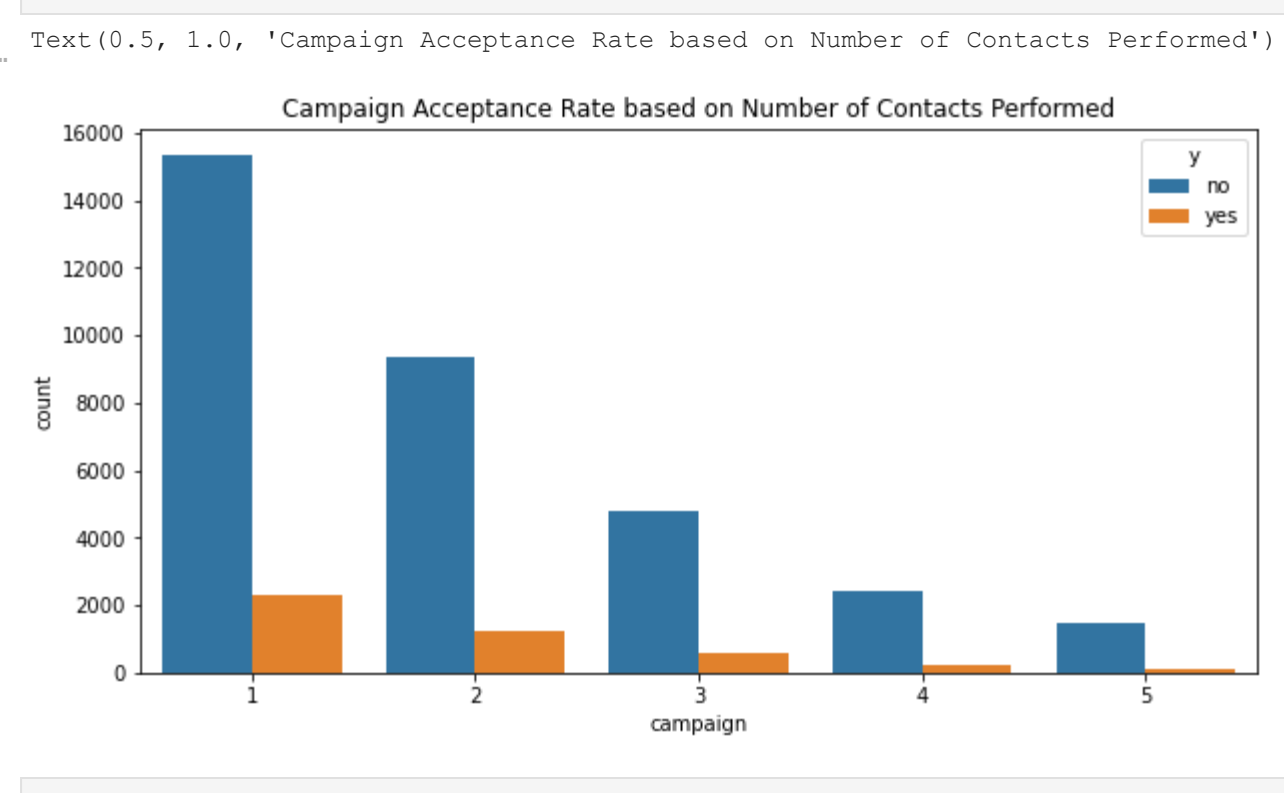


In [707…

```
# Campaign Acceptance rate based of Number of contact performed
fig, ax = plt.subplots(figsize=(10,5))
sns.countplot(data=bank_df, x='campaign', hue='y')
plt.title("Campaign Acceptance Rate based on Number of Contacts Performed")
```

Out[707…

```
Text(0.5, 1.0, 'Campaign Acceptance Rate based on Number of Contacts Performed')
```

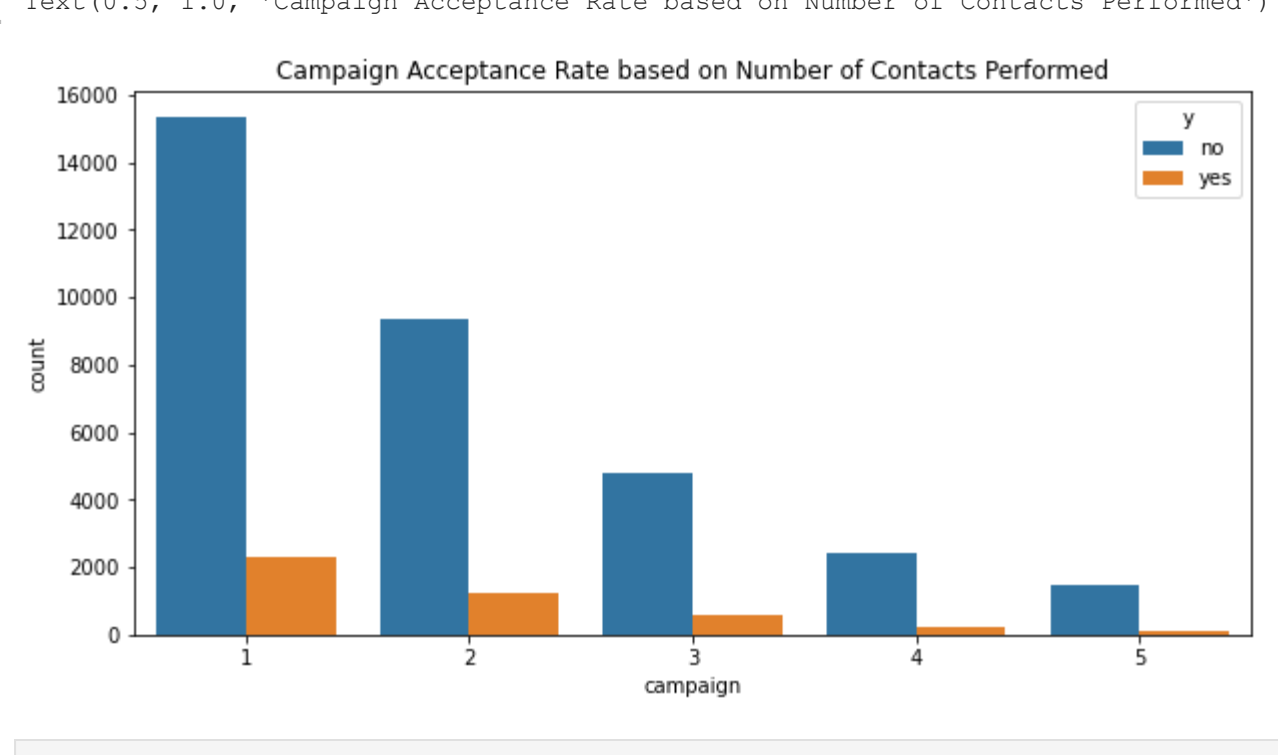


In [708…

```
# Campaign Acceptance rate based of Number of contact performed
fig, ax = plt.subplots(figsize=(10,5))
sns.countplot(data=bank_df, x='campaign', hue='y')
plt.title("Campaign Acceptance Rate based on Number of Contacts Performed")
```

Out[708…

```
Text(0.5, 1.0, 'Campaign Acceptance Rate based on Number of Contacts Performed')
```

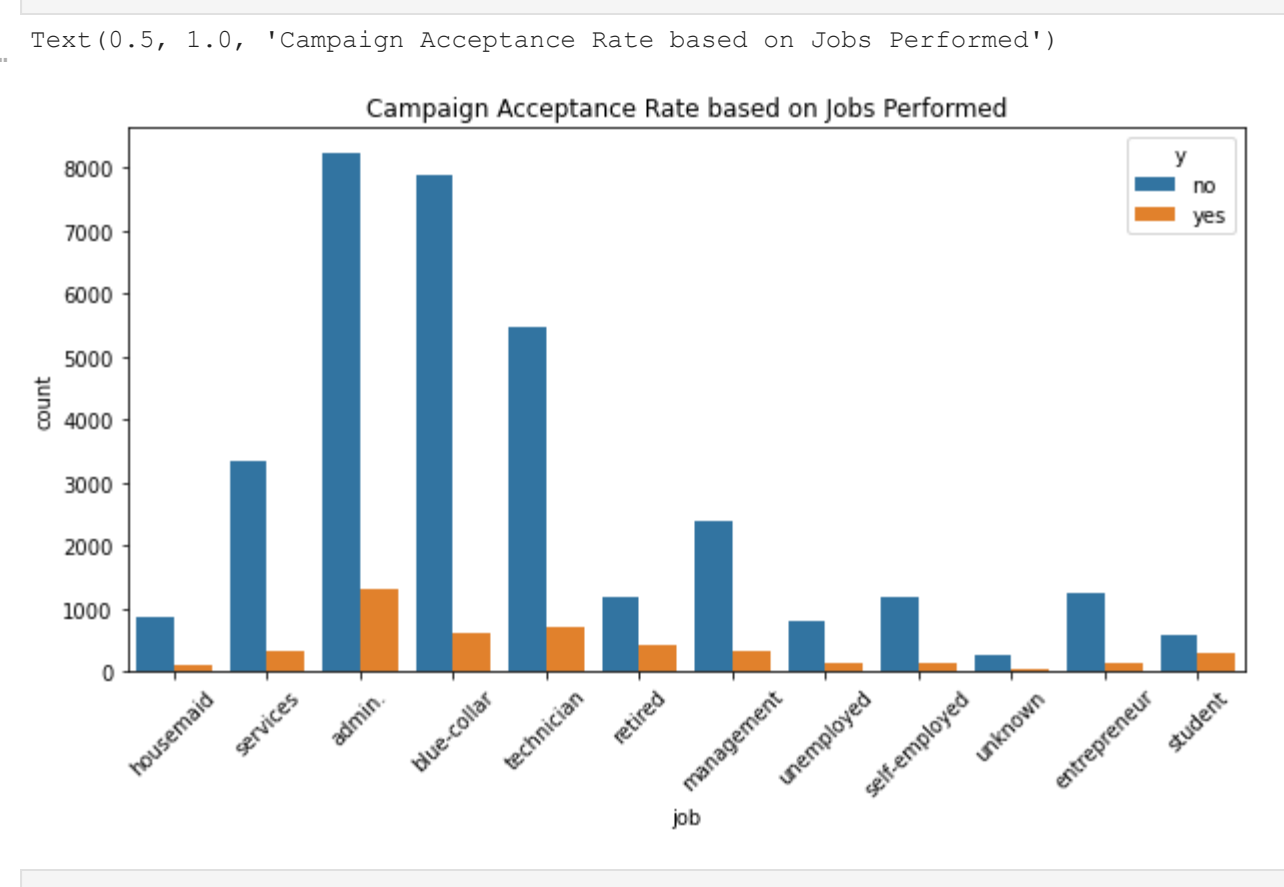


In [709…

```
# Campaign Acceptance rate based of jobs
fig, ax = plt.subplots(figsize=(10,5))
plt.setp(plt.xticks()[1], rotation=45)
sns.countplot(data=bank_df, x='job', hue='y')
plt.title("Campaign Acceptance Rate based on Jobs Performed")
```

Out[709…

```
Text(0.5, 1.0, 'Campaign Acceptance Rate based on Jobs Performed')
```

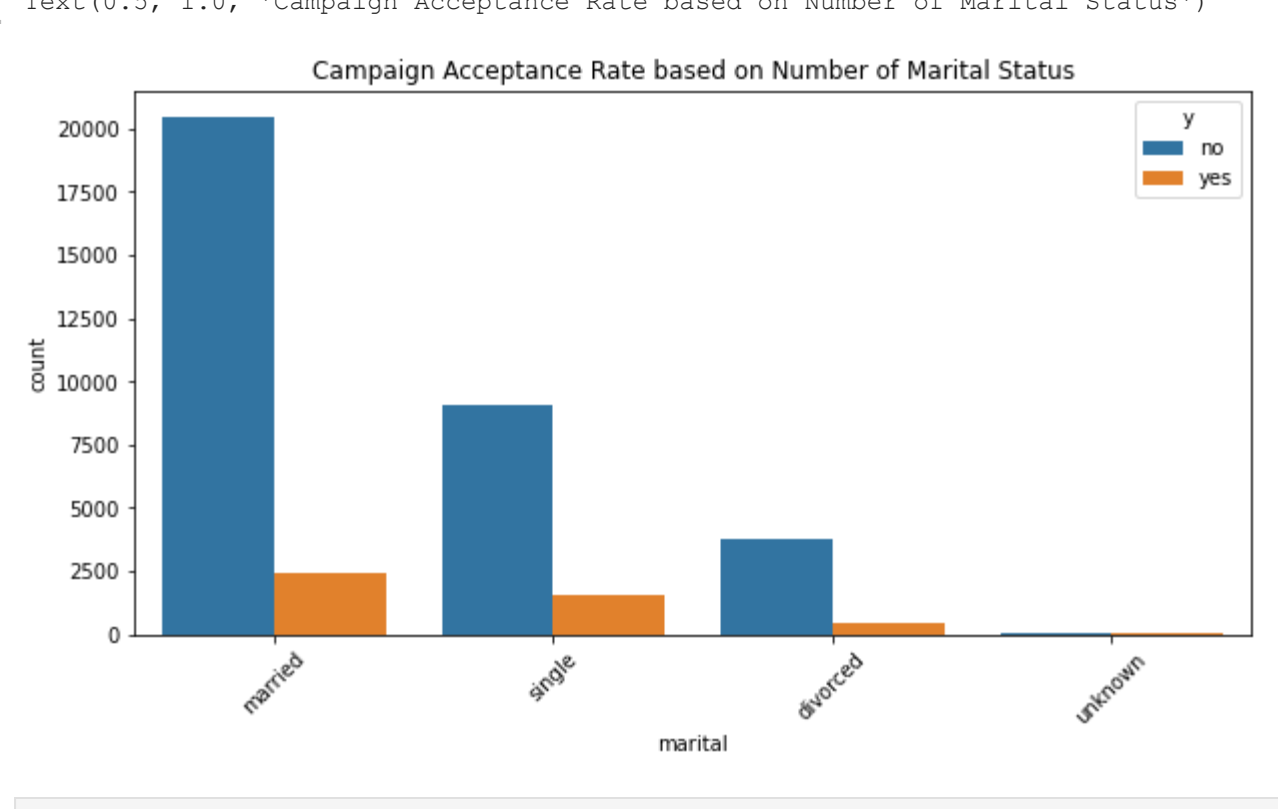


In [710…

```
# Campaign Acceptance rate based of Marital Status
fig, ax = plt.subplots(figsize=(10,5))
plt.setp(plt.xticks()[1], rotation=45)
sns.countplot(data=bank_df, x='marital', hue='y')
plt.title("Campaign Acceptance Rate based on Number of Marital Status")
```

Out[710…

```
Text(0.5, 1.0, 'Campaign Acceptance Rate based on Number of Marital Status')
```

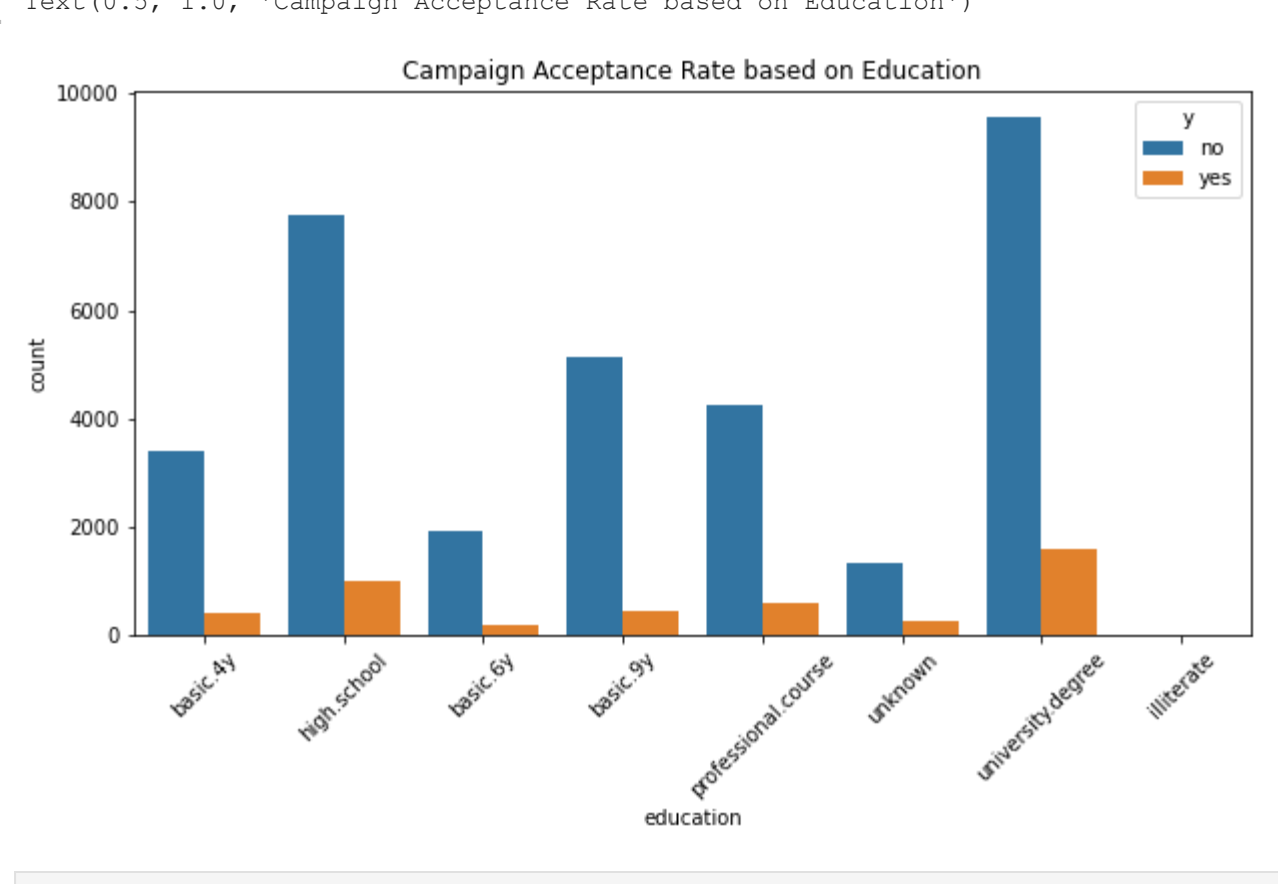


In [711…

```
# Campaign Acceptance rate based of Education
fig, ax = plt.subplots(figsize=(10,5))
plt.setp(plt.xticks()[1], rotation=45)
sns.countplot(data=bank_df, x='education', hue='y')
plt.title("Campaign Acceptance Rate based on Education")
```

Out[711…

```
Text(0.5, 1.0, 'Campaign Acceptance Rate based on Education')
```

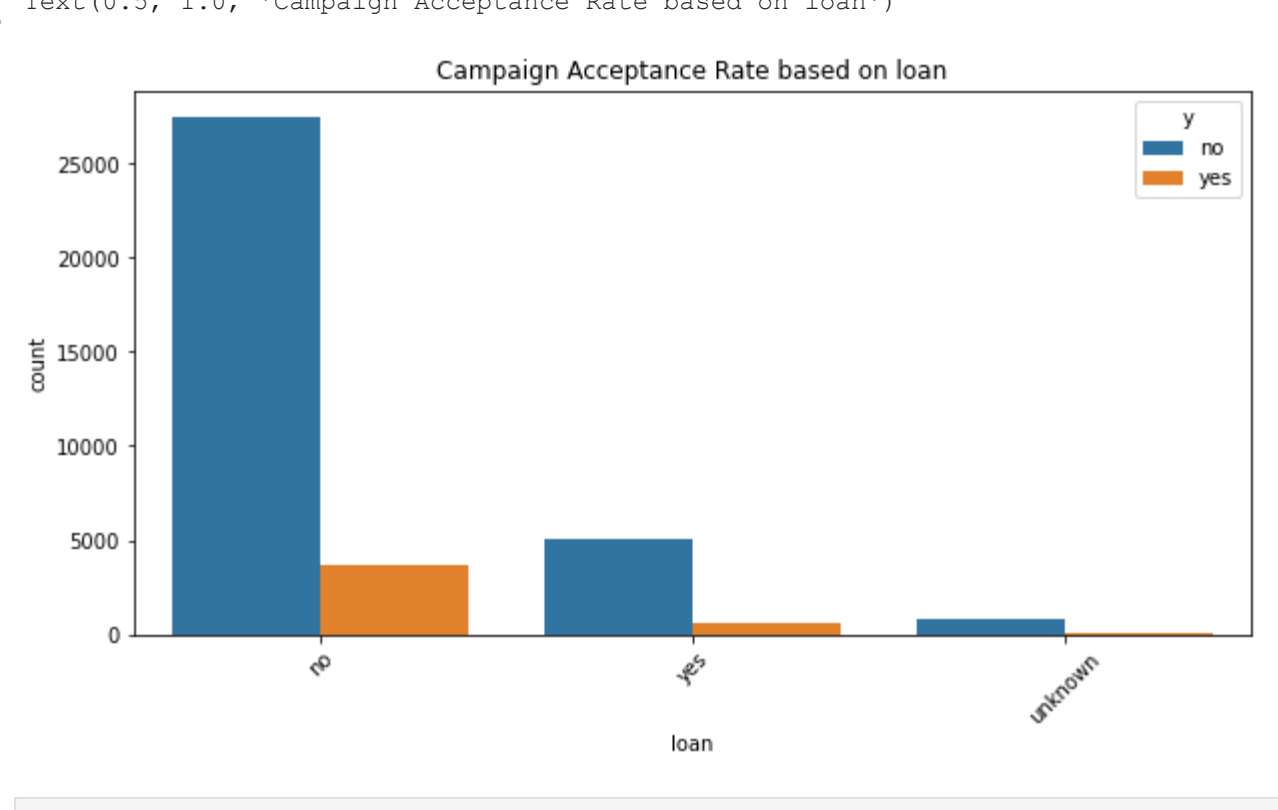


In [712…

```
# Campaign Acceptance rate based of Education
fig, ax = plt.subplots(figsize=(10,5))
plt.setp(plt.xticks()[1], rotation=45)
sns.countplot(data=bank_df, x='loan', hue='y')
plt.title("Campaign Acceptance Rate based on loan")
```

Out[712…

```
Text(0.5, 1.0, 'Campaign Acceptance Rate based on loan')
```

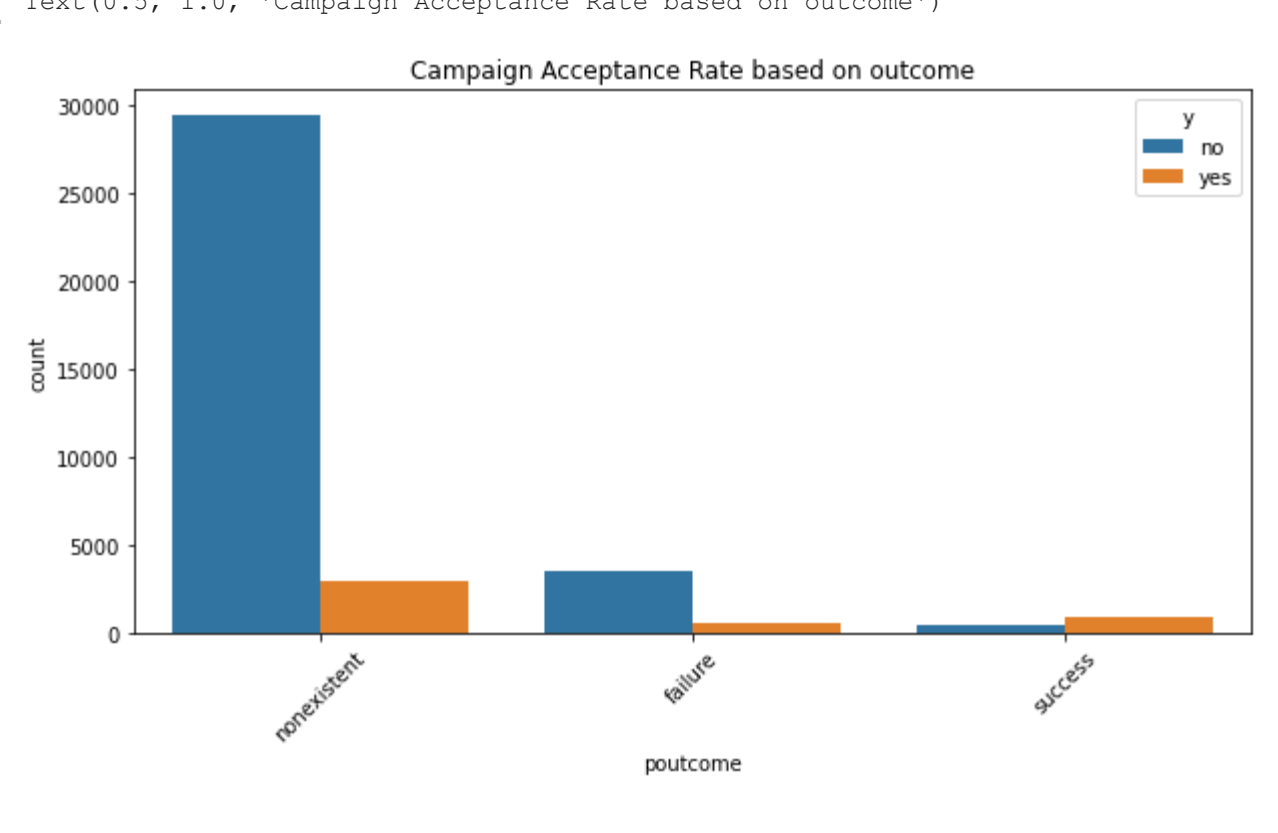


In [713…

```
# Campaign Acceptance rate based of Education
fig, ax = plt.subplots(figsize=(10,5))
plt.setp(plt.xticks()[1], rotation=45)
sns.countplot(data=bank_df, x='poutcome', hue='y')
plt.title("Campaign Acceptance Rate based on outcome")
```

Out[713…

```
Text(0.5, 1.0, 'Campaign Acceptance Rate based on outcome')
```



Problem 5: Engineering Features

Now that you understand your business objective, we will build a basic model to get started. Before we can do this, we must work to encode the data. Using just the bank information features (columns 1 - 7), prepare the features and target column for modeling with appropriate encoding and transformations.

In [714…

```
#Converting Categorical Columns to Numerical Columns using Target Encoder
encoder = preprocessing.LabelEncoder()
encoder_df = bank_df.copy()
def target_encoder(data):
    impute_ordinal = encoder.fit_transform(data)
    data.loc[data.notnull()] = np.squeeze(impute_ordinal)
    return data

for i in tqdm(range(len(cat_cols))):
    target_encoder(encoder_df[cat_cols[i]])
```

```
  0%|          | 0/11 [00:00<?, ?it/s]<ipython-input-714-a6fc6193fbfe>:6: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#ret
urning-a-view-versus-a-copy
  data.loc[data.notnull()] = np.squeeze(impute_ordinal)
100%|██████████| 11/11 [00:00<00:00, 140.15it/s]
```

In [715…

```
encoder_df.describe()
```

Out[715…

	age	duration	campaign	pdays	previous	emp.var.rate	cons.price.idx	cons.conf.idx	euribor3
count	37803.000000	37803.000000	37803.000000	37803.000000	37803.000000	37803.000000	37803.000000	37803.000000	37803.0000
mean	40.007142	263.432717	1.941751	960.176653	0.181785	0.028646	93.560179	-40.485398	3.5691
std	10.458787	259.254134	1.125077	192.472059	0.506630	1.583386	0.581213	4.693541	1.7483
min	17.000000	0.000000	1.000000	0.000000	0.000000	-3.400000	92.201000	-50.800000	0.6340
25%	32.000000	107.000000	1.000000	999.000000	0.000000	-1.800000	93.075000	-42.700000	1.3340
50%	38.000000	185.000000	2.000000	999.000000	0.000000	1.100000	93.444000	-41.800000	4.8570
75%	47.000000	324.000000	3.000000	999.000000	0.000000	1.400000	93.994000	-36.400000	4.9610
max	98.000000	4918.000000	5.000000	999.000000	7.000000	1.400000	94.767000	-26.900000	5.0450

In [716…

```
encoder_df = encoder_df.drop('duration', axis=1)
```

In [717…

```
encoder_df.reset_index()
```

Out[717…

	index	age	job	marital	education	default	housing	loan	contact	month	...	campaign	pdays	previous	poutcome	emp.var.ra
0	0	56	3	1	0	0	0	0	1	6	...	1	999	0	1	
1	1	57	7	1	3	1	0	0	1	6	...	1	999	0	1	
2	2	37	7	1	3	0	2	0	1	6	...	1	999	0	1	
3	3	40	0	1	1	0	0	0	1	6	...	1	999	0	1	
4	4	56	7	1	3	0	0	2	1	6	...	1	999	0	1	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
37798	41183	73	5	1	5	0	2	0	0	7	...	1	999	0	1	-
37799	41184	46	1	1	5	0	0	0	0	7	...	1	999	0	1	-
37800	41185	56	5	1	6	0	2	0	0	7	...	2	999	0	1	-
37801	41186	44	9	1	5	0	0	0	0	7	...	1	999	0	1	-
37802	41187	74	5	1	5	0	2	0	0	7	...	3	999	1	0	-

37803 rows × 21 columns

In [718…

```
#standardizing the dataset
scaler = preprocessing.StandardScaler()
std_df = scaler.fit_transform(encoder_df.drop(['job', 'marital', 'education', 'default', 'housing', 'loan', 'co
scaled_df = pd.DataFrame(std_df, columns=['age','pdays','cons.price.idx','cons.conf.idx','euribor3m','nr.employ
```

In [719…

```
scaled_df = pd.DataFrame(std_df, columns=['age','pdays','cons.price.idx','cons.conf.idx','euribor3m','nr.employ
```

In [720…

```
scaled_df['job'] = encoder_df['job'].values
scaled_df['marital'] = encoder_df['marital'].values
scaled_df['education'] = encoder_df['education'].values
scaled_df['default'] = encoder_df['default'].values
scaled_df['housing'] = encoder_df['housing'].values
scaled_df['loan'] = encoder_df['loan'].values
scaled_df['contact'] = encoder_df['contact'].values
scaled_df['month'] = encoder_df['month'].values
scaled_df['day_of_week'] = encoder_df['day_of_week'].values
scaled_df['campaign'] = encoder_df['campaign'].values
scaled_df['previous'] = encoder_df['previous'].values
scaled_df['poutcome'] = encoder_df['poutcome'].values
scaled_df['emp.var.rate'] = encoder_df['emp.var.rate'].values
scaled_df['y'] = encoder_df['y'].values
```

In [721…

```
scaled_df.head()
```

Out[721…

	age	pdays	cons.price.idx	cons.conf.idx	euribor3m	nr.employed	job	marital	education	default	housing	loan	contact	mo
0	1.529151	0.201712	0.746417	0.870441	0.736639	0.360955	3	1	0	0	0	0	1	
1	1.624766	0.201712	0.746417	0.870441	0.736639	0.360955	7	1	3	1	0	0	1	
2	-0.287527	0.201712	0.746417	0.870441	0.736639	0.360955	7	1	3	0	2	0	1	
3	-0.000683	0.201712	0.746417	0.870441	0.736639	0.360955	0	1	1	0	0	0	1	
4	1.529151	0.201712	0.746417	0.870441	0.736639	0.360955	7	1	3	0	0	2	1	

In [722…

```
scaled_df.describe()
```

Out[722…

	age	pdays	cons.price.idx	cons.conf.idx	euribor3m	nr.employed	campaign	previous	emp.var
count	3.780300e+04	3.780300e+04	3.780300e+04	37803.000000	3.780300e+04	3.780300e+04	37803.000000	37803.000000	37803.00
mean	3.247938e-16	-7.217639e-17	-1.814033e-14	0.000000	2.405880e-17	4.811759e-16	1.941751	0.181785	0.02
std	1.000013e+00	1.000013e+00	1.000013e+00	1.000013	1.000013e+00	1.000013e+00	1.125077	0.506630	1.58
min	-2.199820e+00	-4.988721e+00	-2.338552e+00	-2.197645	-1.678834e+00	-2.752819e+00	1.000000	0.000000	-3.40
25%	-7.656001e-01	2.017117e-01	-8.347802e-01	-0.471847	-1.278447e+00	-8.974258e-01	1.000000	0.000000	-1.80
50%	-1.919122e-01	2.017117e-01	-1.998926e-01	-0.280091	7.366394e-01	3.609552e-01	2.000000	0.000000	1.10
75%	6.686196e-01	2.017117e-01	7.464167e-01	0.870441	7.961253e-01	8.689632e-01	3.000000	0.000000	1.40
max	5.544967e+00	2.017117e-01	2.076411e+00	2.894526	8.441717e-01	8.689632e-01	5.000000	7.000000	1.40

Problem 6: Train/Test Split

With your data prepared, split it into a train and test set.

In [723…

```
X = scaled_df.drop('y', axis=1)
y = scaled_df["y"].astype('int')
print(X.shape)
print(y.shape)
```

```
(37803, 19)
(37803,)
```

In [724…

```
X_train,X_test, y_train, y_test = train_test_split(X, y, test_size=0.33, random_state=42)
```

In [725…

```
print(X_train.shape)
print(y_train.shape)
print(X_test.shape)
print(y_test.shape)
```

```
(25328, 19)
(25328,)
(12475, 19)
(12475,)
```

In [ ]:

Problem 7: A Baseline Model

Before we build our first model, we want to establish a baseline. What is the baseline performance that our classifier should aim to beat?

In [726…

```
models = ['Baseline']
train_time = []
train_accuracy = []
test_accuracy = []
accuracy_score = []
AUC_score = []
```

In [727…

```
# Baseline Model
dummy_clf = DummyClassifier( random_state=42)
start_time = time()
dummy_clf.fit(X_train, y_train)
train_time.append(time() - start_time)
# Training
y_preds = dummy_clf.predict(X_train)
training_score = dummy_clf.score(X_train, y_train)
train_accuracy.append('training_score')
# Test score
y_preds_test = dummy_clf.predict(X_test)
test_score = dummy_clf.score(X_test, y_test)
test_accuracy.append(test_score)
accuracy_score.append('N/A')
AUC_score.append('N/A')
```

Problem 8: A Simple Model

Use Logistic Regression to build a basic model on your data.

In [728…

```
# Logistics Regression Model
models.append('Logistics Regression')
log_reg = LogisticRegression(solver='liblinear', random_state=42)
start_time = time()
log_reg.fit(X_train, y_train)
train_time.append(time() - start_time)
y_preds_log_reg = log_reg.predict(X_test)
```

Problem 9: Score the Model

What is the accuracy of your model?

In [729…

```
train_score = log_reg.score(X_train, y_train)
train_accuracy.append(train_score)
test_accuracy.append(log_reg.score(X_test, y_test))
#accuracy scores
accuracy_score.append(metrics.accuracy_score(y_test, y_preds_log_reg))
fpr, tpr, _thresholds = metrics.roc_curve(y_test, y_preds_log_reg)
AUC_score.append(metrics.auc(fpr, tpr))
```

In [730…

```
print('Precision    : %.3f'%precision_score(y_test, y_preds_log_reg))
print('Recall       : %.3f'%recall_score(y_test, y_preds_log_reg))
print('F1 Score     : %.3f'%f1_score(y_test, y_preds_log_reg))
```

```
Precision    : 0.665
Recall       : 0.237
F1 Score     : 0.349
```

In [731…

```
from sklearn.metrics import confusion_matrix
confusion_matrix = confusion_matrix(y_test, y_test_preds)
print(confusion_matrix)
```

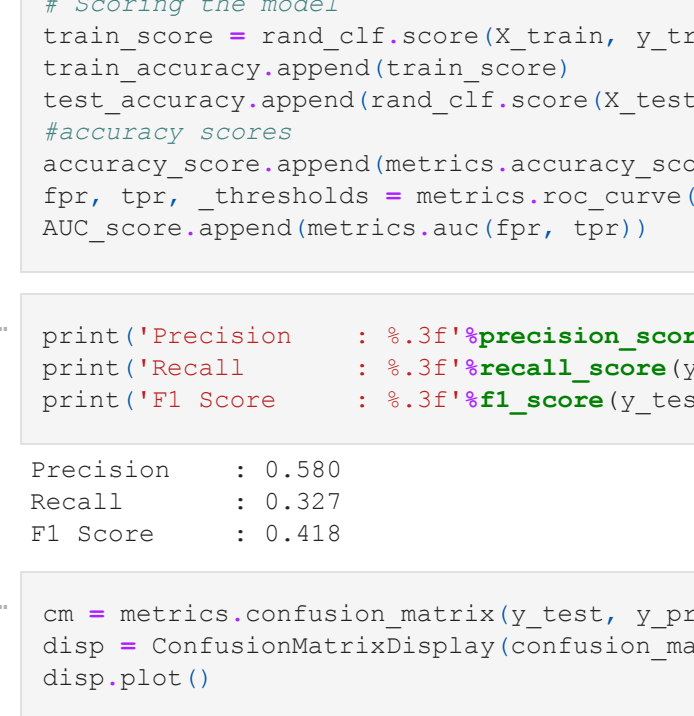
```
[[10803   178]
 [ 1140   354]]
```

In [732…

```
disp = ConfusionMatrixDisplay(confusion_matrix=confusion_matrix)
disp.plot()
```

Out[732…

```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x144d651f0>
```



Problem 10: Model Comparisons

Now, we aim to compare the performance of the Logistic Regression model to our KNN algorithm, Decision Tree, and SVM models. Using the default settings for each of the models, fit and score each. Also, be sure to compare the fit time of each of the models. Present your findings in a `DataFrame` similar to that below:

Model	Train Time	Train Accuracy	Test Accuracy
	.	.	

RandomForestClassifier

In [733…

```
models.append('RandomForestClassifier')
rand_clf = RandomForestClassifier(random_state=42)
start_time = time()
rand_clf.fit(X_train, y_train)
train_time.append(time() - start_time)
y_pred_rand_clf = rand_clf.predict(X_test)
```

In [734…

```
# Scoring the model
train_score = rand_clf.score(X_train, y_train)
train_accuracy.append(train_score)
test_accuracy.append(rand_clf.score(X_test, y_test))
#accuracy scores
accuracy_score.append(metrics.accuracy_score(y_test, y_pred_rand_clf))
fpr, tpr, _thresholds = metrics.roc_curve(y_test, y_pred_rand_clf)
AUC_score.append(metrics.auc(fpr, tpr))
```

In [735…

```
print('Precision    : %.3f'%precision_score(y_test, y_pred_rand_clf))
print('Recall       : %.3f'%recall_score(y_test, y_pred_rand_clf))
print('F1 Score     : %.3f'%f1_score(y_test, y_pred_rand_clf))
```

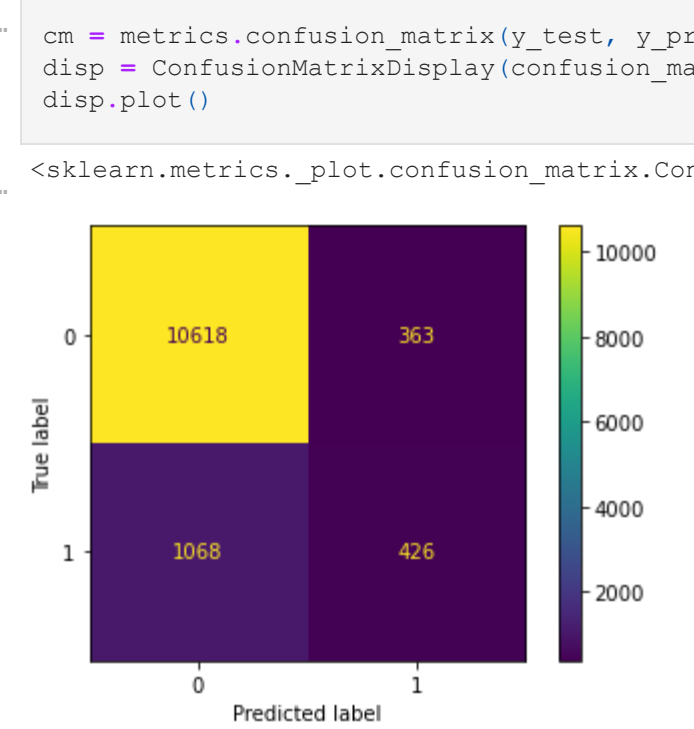
```
Precision    : 0.580
Recall       : 0.327
F1 Score     : 0.418
```

In [736…

```
cm = metrics.confusion_matrix(y_test, y_pred_rand_clf)
disp = ConfusionMatrixDisplay(confusion_matrix=cm)
disp.plot()
```

Out[736…

```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x1461adcd0>
```



In [ ]:

KNeighborsClassifier

In [737…

```
models.append('KNeighborsClassifier')
knn = KNeighborsClassifier()
start_time = time()
knn.fit(X_train, y_train)
train_time.append(time() - start_time)
y_pred_knn = knn.predict(X_test)
```

In [738…

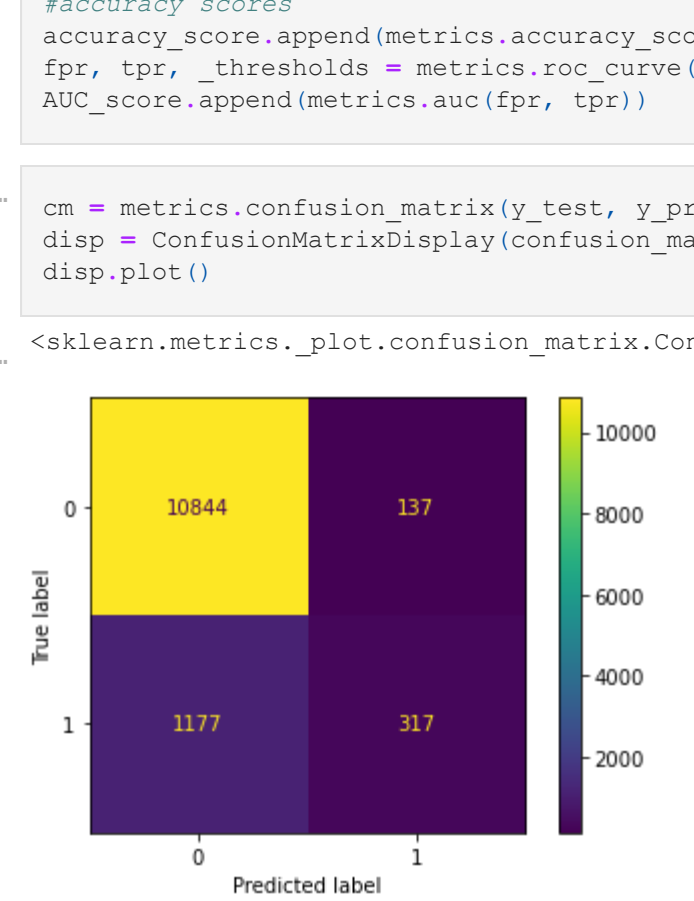
```
# Scoring the model
train_score = knn.score(X_train, y_train)
train_accuracy.append(train_score)
test_accuracy.append(knn.score(X_test, y_test))
#accuracy scores
accuracy_score.append(metrics.accuracy_score(y_test, y_pred_knn))
fpr, tpr, _thresholds = metrics.roc_curve(y_test, y_pred_knn)
AUC_score.append(metrics.auc(fpr, tpr))
```

In [739…

```
cm = metrics.confusion_matrix(y_test, y_pred_knn)
disp = ConfusionMatrixDisplay(confusion_matrix=cm)
disp.plot()
```

Out[739…

```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x1460d29d0>
```



In [740…

```
print('Precision    : %.3f'%precision_score(y_test, y_pred_knn))
print('Recall       : %.3f'%recall_score(y_test, y_pred_knn))
print('F1 Score     : %.3f'%f1_score(y_test, y_pred_knn))
```

```
Precision    : 0.540
Recall       : 0.285
F1 Score     : 0.373
```

SVC

In [741…

```
models.append('SVC')
svc = SVC()
start_time = time()
svc.fit(X_train, y_train)
train_time.append(time() - start_time)
y_pred_svc = svc.predict(X_test)
```

In [742…

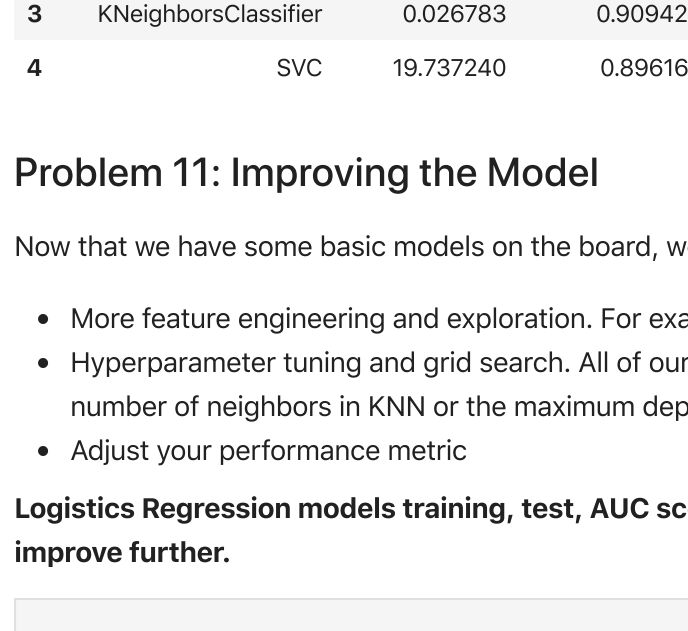
```
# Scoring the model
train_score = svc.score(X_train, y_train)
train_accuracy.append(train_score)
test_accuracy.append(svc.score(X_test, y_test))
#accuracy scores
accuracy_score.append(metrics.accuracy_score(y_test, y_pred_svc))
fpr, tpr, _thresholds = metrics.roc_curve(y_test, y_pred_svc)
AUC_score.append(metrics.auc(fpr, tpr))
```

In [743…

```
cm = metrics.confusion_matrix(y_test, y_pred_svc)
disp = ConfusionMatrixDisplay(confusion_matrix=cm)
disp.plot()
```

Out[743…

```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x146891460>
```



In [744…

```
print('Precision    : %.3f'%precision_score(y_test, y_pred_knn))
print('Recall       : %.3f'%recall_score(y_test, y_pred_knn))
print('F1 Score     : %.3f'%f1_score(y_test, y_pred_knn))
```

```
Precision    : 0.540
Recall       : 0.285
F1 Score     : 0.373
```

In [745…

```
model_artifacts = pd.DataFrame({'Model':models,
                                'Training_Time':train_time,
                                'Training_Score': train_accuracy,
                                'Test_Score':test_accuracy,
                                'Accuracy': accuracy_score,
                                'AUC': AUC_score})
model_artifacts
```

Out[745…

	Model	Training_Time	Training_Score	Test_Score	Accuracy	AUC
0	Baseline	0.001680	training_score	0.880240	N/A	N/A
1	Logistics Regression	0.164353	0.89711	0.894349	0.894349	0.610369
2	RandomForestClassifier	1.631834	0.994709	0.891062	0.891062	0.647536
3	KNeighborsClassifier	0.026783	0.909428	0.885291	0.885291	0.626042
4	SVC	19.737240	0.896162	0.894669	0.894669	0.599853

Problem 11: Improving the Model

Now that we have some basic models on the board, we want to try to improve these. Below, we list a few things to explore in this pursuit.

- More feature engineering and exploration. For example, should we keep the gender feature? Why or why not?
- Hyperparameter tuning and grid search. All of our models have additional hyperparameters to tune and explore. For example the number of neighbors in KNN or the maximum depth of a Decision Tree.
- Adjust your performance metric

Logistics Regression models training, test, AUC scores better than other models. Optimizing Logistics Regression models to improve further.

In [746…

```
grid={"C":np.logspace(-3,3,7), "penalty":["l1","l2"]}
log_reg = LogisticRegression()
lgr_cv=GridSearchCV(lgr, grid, cv=10)
lgr_cv.fit(X_train, y_train)
```

Out[746…

```
GridSearchCV(cv=10,
             estimator=LogisticRegression(random_state=41, solver='liblinear'),
             param_grid={'C': array([1.e-03, 1.e-02, 1.e-01, 1.e+00, 1.e+01, 1.e+02, 1.e+03]),
                         'penalty': ['l1', 'l2']})
```

In [747…

```
lgr_cv.best_params_
```

Out[747…

```
{'C': 0.1, 'penalty': 'l1'}
```

In [748…

```
#Adjust Performance Metrics
lgr2=LogisticRegression(C=0.1, penalty="l2", solver='liblinear')
start_time = time()
lgr2.fit(X_train,y_train)
train_time = time() - start_time
```

In [749…

```
y_pred = lgr2.predict(X_test)
```

In [750…

```
cm = metrics.confusion_matrix(y_test, y_pred)
```

In [751…

```
disp = ConfusionMatrixDisplay(confusion_matrix=cm)
disp.plot()
```

Out[751…

```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x15c66a6d0>
```


In [752…

```
print('Precision    : %.3f'%precision_score(y_test, y_pred))
print('Recall       : %.3f'%recall_score(y_test, y_pred))
print('F1 Score     : %.3f'%f1_score(y_test, y_pred))
```

```
Precision    : 0.657
Recall       : 0.234
F1 Score     : 0.345
```

In [ ]:

In [ ]:

In [ ]:

Questions